

1 WHAT IS CLAIMED IS:

- 2 1. A system for controlling particle accelerators, comprising:
3 a distributed control system that further comprises:
4 a computing device operable to execute a first software
5 tool that identifies variable inputs and controlled
6 variables associated with the particle accelerator, wherein
7 at least one variable input is a manipulated variable
8 input, and wherein said first software tool is further
9 operable to determine relationships between said variable
10 inputs and said controlled variables; and
11 at least one input/output controller operable to monitor
12 said variable inputs and tune said manipulated variable to
13 achieve a desired controlled variable value.
- 14 2. The system for controlling particle accelerators of Claim
15 1, wherein said relationships between said variable input
16 parameters and said controlled variables comprises a first
17 principle models wherein said first principle model is
18 dependent on said variable inputs.
- 19 3. The system for controlling particle accelerators of Claim
20 1, further comprising neural networks utilized to identify
21 said variable inputs.
- 22 4. The system for controlling within particle accelerators of
23 Claim 1, wherein said step of determining relationships

1 between said variable inputs and said controlled variables
2 utilizes a combination of physical models and empirical
3 methods.

4 5. The system for controlling particle accelerators of Claim
5 4, wherein said physical models and empirical methods are
6 combined in series.

7 6. The system for controlling particle accelerators of Claim
8 4, wherein said physical models and empirical methods are
9 combined in parallel.

10 7. The system for controlling particle accelerators of Claim
11 4, wherein said physical model varies over an operating
12 range..

13 8. The system for controlling particle accelerators of Claim
14 5, wherein said physical model is a function of said
15 variable inputs.

16 9. The system for controlling particle accelerators of
17 claim 7, wherein said physical model comprises first
18 principle parameters which vary with said variable inputs,
19 wherein empirical methods comprise a neural network used to
20 identify first principle parameters values associated with
21 said variable inputs, and wherein said neural network

1 updates said first principle parameters with values
2 associated with said variable inputs.

3 10. The system for controlling particle accelerators of Claim
4 9, wherein said neural network is trained.

5 11. The system for controlling particle accelerators of Claim
6 9, wherein said neural network is trained according to at
7 least one method selected from the group consisting of:
8 gradient methods, back propagation, gradient-based
9 nonlinear programming methods, sequential quadratic
10 programming, generalized reduced gradient methods, and non-
11 gradient methods.

12 12. The system for controlling particle accelerators of Claim
13 11, wherein gradient methods require gradients of an error
14 with respect to a weight and bias obtained by numerical
15 derivatives.

16 13. The system for controlling particle accelerators of Claim
17 11, wherein gradient methods require gradients of an error
18 with respect to a weight and bias obtained by analytical
19 derivatives.

20 14. The system for controlling particle accelerators of Claim
21 10, wherein said controlled variable comprises a magnetic
22 field strength, shape, location and/or orientation and said

1 controlled variable comprises particle positions within
2 said particle accelerator.

3 15. The system for controlling nonlinear control problems
4 within particle accelerators of Claim 14, wherein said step
5 of tuning said manipulated variable comprises adjusting a
6 connector magnet and/or quadrupole magnet.

7 16. A dynamic controller for controlling the operation of a
8 particle accelerator by predicting a change in the dynamic
9 variable input values to the process to effect a change in
10 the output of the particle accelerator from a current
11 output value at a first time to a different and desired
12 output value at a second time to achieve more efficient
13 collisions between particles, comprising:
14 a dynamic predictive model for receiving the current
15 variable input value, wherein said dynamic predictive model
16 changes dependent upon said input value, and the desired
17 output value, and wherein said dynamic predictive model
18 produces a plurality of desired controlled variable values
19 at different time positions between the first time and the
20 second time to define a dynamic operation path of the
21 particle accelerator between the current output value and
22 the desired output value at the second time; and

1 an optimizer for optimizing the operation of the dynamic
2 controller over a plurality of the different time positions
3 in accordance with a predetermined optimization method that
4 optimizes the objectives of the dynamic controller to
5 achieve a desired path, such that the objectives of the
6 dynamic predictive model vary as a function of time.

7 17. The dynamic controller of claim 16, wherein said dynamic
8 predictive model comprises:

9 a dynamic forward model operable to receive variable input
10 values at each of said time positions and map said variable
11 input values to components of said dynamic predictive model
12 associated with said received variable input values in
13 order to provide a predicted dynamic output value;

14 an error generator for comparing the predicted dynamic
15 output value to the desired output value and generating a
16 primary error value as the difference for each of said time
17 positions;

18 an error minimization device for determining a change in
19 the variable input value to minimize the primary error
20 value output by said error generator;

21 a summation device for summing said determined variable
22 input change value with an original variable input value,
23 which original variable input value comprises the variable
24 input value before the determined change therein, for a

1 plurality of time position to provide a future variable
2 input value as a summed variable input value; and
3 a controller for controlling the operation of said error
4 minimization device to operate under control of said
5 optimizer to minimize said primary error value in
6 accordance with said optimization method.

7 18. A method for controlling particle accelerators, comprising
8 the steps of:
9 identifying variable inputs and controlled variables
10 associated with the particle accelerator, wherein at least
11 one variable input parameter is a manipulated variable;
12 determining relationships between said variable inputs and
13 said controlled variables wherein said relationship
14 comprises models, and wherein parameters within said model
15 are dependent on said variable inputs; and
16 tuning said manipulated variable to achieve a desired
17 controlled variable value.

18 19. The method of Claim 18, wherein said step of
19 identifying parameters utilizes neural networks to identify
20 said parameters.

21 20. The method of Claim 18, wherein said step of identifying
22 parameters utilizes neural networks that identify said
23 parameters when an operating region changes.

1 21. The method of Claim 18, wherein said step of identifying
2 parameters utilizes neural networks that identify said
3 parameters.

4 22. The method of Claim 18, wherein said step of determining
5 relationships between said variable inputs and said
6 controlled variables utilizes a combination of physical
7 models and empirical methods.

8 23. The method of Claim 22, wherein said physical models and
9 empirical methods are combined in series.

10 24. The method of Claim 22, wherein said physical models and
11 empirical methods are combined in parallel.

12 25. The method of Claim 22, wherein said physical model varies
13 over an operating range.

14 26. The method of Claim 25, wherein said physical model is a
15 function of said variable inputs.

16 27. The method of Claim 26, wherein said physical model
17 comprises first principle parameters which vary with said
18 variable inputs, wherein empirical methods comprise a
19 neural network used to identify first principle parameter
20 values associated with said variable inputs , and wherein

1 said neural network updates said first principle parameters
2 with values associated with said variable inputs.

3 28. The method of Claim 27, wherein said neural network is
4 trained.

5 29. The method of Claim 28, wherein said neural network is
6 trained according to at least one method selected from the
7 group consisting of gradient methods, back propagation,
8 gradient-based nonlinear programming (NLP) methods,
9 sequential quadratic programming, generalized reduced
10 gradient methods, and non-gradient methods.

11 30. The method of Claim 29, wherein gradient methods require
12 gradients of an error with respect to a weight and bias
13 obtained by either numerical derivatives or analytical
14 derivatives.

15 31. The method of Claim 18, wherein said manipulated variable
16 comprises a magnetic field strength, shape, location and/or
17 orientation and said controlled variable comprises particle
18 positions within said particle accelerator.

19 32. The method of Claim 31, wherein said step of tuning said
20 manipulated variable comprises adjusting a connector
21 magnet.

1 33. The method of Claim 31, wherein said step of tuning said
2 manipulated variable comprises adjusting and quadrapole
3 magnet.

4 34. The method of Claim 31, wherein said step of tuning said
5 manipulated variable comprises adjusting a connector magnet
6 and quadrapole magnet.